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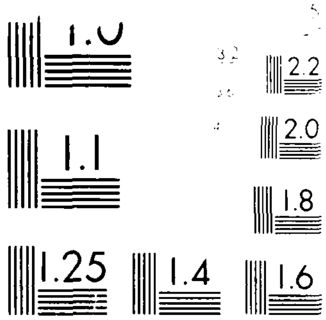
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PREDICTING LIFE OF ELECTRIC VEHICLE AND LOAD-LEVELING LEAD ACID BATTERIES FROM INITIAL ACCEPTANCE TEST DATA BY USE OF PATTERN RECOGNITION ANALYSIS

S. P. Perone
Chemistry & Materials Science Department
Lawrence Livermore National Laboratory
P. O. Box 808
Livermore, CA 94550

and

W. C. Spindler
Electric Power Research Institute
P. O. BOX 10412
Palo Alto, CA 94303

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A novel approach to battery lifetime prediction was applied to life-cycling data for 108 ESB EV-106 6-V golf cart batteries (tests conducted by TRW for NASA-Lewis). Computerized pattern recognition methods were used to examine initial cycling measurements and to classify individual batteries into "long-lived" or "short-lived" classes with greater than 85% accuracy. Results of this study were used to design a fabrication and test program for 340 GNB

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ABSTRACT

A novel approach to battery lifetime prediction was applied to life-cycling data for 108 ESB EV-106 6-V golf cart batteries (tests conducted by TRW for NASA-Lewis). Computerized pattern recognition methods were used to examine initial cycling measurements and to classify individual batteries into "long-lived" or "short-lived" classes with greater than 85% accuracy. Results of this study were used to design a fabrication and test program for 340 GNB lead-acid cells in a 500 kWh load-leveling battery to be tested at the Battery Energy Storage Test Facility. Preliminary observations on initial test data are reported here.

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INTRODUCTION

The concept of lifetime prediction of individual cells was explored previously by Byers and Perone (1979) for sealed Ni/Cd space cells tested at Crane Naval Weapons Support Center. The basic approach involved the use of pattern recognition techniques to determine if measurements of cell initial characteristics could be used to predict lifetime. The results of this initial study demonstrated that cells from the same production lot, with similar fabrication and operational conditions, could be categorized as "short-lived" or "long-lived" from initial measurements with virtually 100% accuracy.

It is the primary goal of the studies reported here to investigate the general applicability of these lifetime prediction techniques to lead-acid batteries. The first study examined life-cycling data collected for 108 golf cart batteries. A second study has begun involving the analysis of fabrication and initial test data for 340 large motive power lead-acid cells. A unique attribute of this later study is that the authors provided guidance for the fabrication procedures and initial test repertoire, based on results of the earlier study, to provide the most useful information for lifetime prediction.

PATTERN RECOGNITION METHODS

Classification Procedures.

Two different techniques were used for pattern recognition lifetime prediction: Linear Discriminant Analysis (LDA); and k-Nearest Neighbor analysis (kNN), (Nilsson, 1965; Fu, 1968; Andrews, 1972; Fukunaga, 1972; Duda and Hart, 1973; Varmuza, 1980). The LDA method allows accurate classification when classes can be separated by a linear boundary (line, plane,

hyperplane) in feature space. The kNN method classifies each pattern based on the class of its k nearest neighbors in feature space.

Feature Selection Techniques.

Feature selection involves reducing the dimensionality of a problem by finding the minimal sub-set of pattern descriptors (features) which are required for classification. Various methods have been used (Brunner, et al, 1974; Kowalski and Bender, 1973; Wangen, et al, 1971; Thomas, et al, 1977) In our work a systematic trial-and-error feature elimination procedure was used (Thomas 1977), guided by visual examination of feature plots.

OBSERVATIONS WITH THE EV-106 BATTERIES

Description of the Data Base

The test program undertaken for NASA-Lewis by TRW (Kraml and Ames, 1982; Ewashinka and Sidik, 1982) was a statistically designed factorial experiment to apply a daily charge/discharge cycle program to 108 lead-acid 6-V batteries until failure. The four conditions controlled included characteristics of a chopper-controlled discharge (frequency, duty cycle); average/peak discharge current; and depth of discharge. The test group was selected from a uniform production run of 120 ESB type EV-106 batteries, based on pretest inspection and several capacity cycles at TRW. This battery has 10 parallel positive plates per cell and is nominally rated at 132 Ah. However, all batteries were in the range of 110 to 120 Ah when cycled for capacity. Thus, the planned 25, 50 and 75% depths of discharge were actually as high as 93%, as pointed out in the TRW/NASA report (Kraml 1982; Ewashinka 1982). It is also important to recognize that the life cycle data reflect the time to failure for the weakest cell of the 3 in each battery.

Over a 2-year life-cycling period 69 percent of the batteries failed. Experimental correlations showed that battery cycle life was inversely proportional to depth of discharge at a high level of statistical significance, and to average discharge current at a marginal level of significance. No other significant effects were detected.

The dominant failure mode observed involved a gradual loss of capacity to the half-capacity failure point. Of the failed batteries, 23 were subjected to autopsies which showed consistent evidence of cell element aging. All 3 cells in each battery examined exhibited short circuits caused by metallic bridging across the plates at separator edges. Except for two early failures due to other causes, every failed item examined exhibited buckled positive plates and oxidized positive grids.

Lifetime Distributions.

Lifetimes of the EV-106 batteries were dependent on depth of discharge (DOD) and on average discharge current (IAV). Figure 1 illustrates the differences for 50% and 75% DOD (Abbreviated DOD50 and DOD75). (The upper block in each case represent items unfailed after 589 cycles.) Each of these distributions could be further sub-divided into sub-sets with 7 values of IAV varying from 20 to 260 A. Unfortunately, these sub-set limits would be too restrictive for analysis of the data base, because no more than 15 items could be included in a single sub-set. Only the 50 and 75% DOD sub-sets had sufficient numbers of failures, 81% and 97%, to be useful for pattern recognition analysis. These were normalized with respect to influential parameters.

Normalized Lifetime Distributions.

Normalization of the cycle-life characteristic was accomplished according to one of two relationships. The first is referred to as "REGLIFE", which is equated to the deviations of observed lifetimes:

$$REGLIFE = FCY - A - B*(IAV)$$

FCY is the number of cycles to failure, and IAV is the average discharge current. The constants A and B are determined from a regression fit to all data where DOD is constant. Then for each failed battery in the DOD sub-set, the value of REGLIFE is calculated. The second normalization function was based on the calculation of a relative lifetime, referred to as "RELIF". It is equated to the ratio of the observed lifetime for a specific battery to the average lifetime for all other batteries where DOD and IAV are the same.

$$RELIF = FCY/AVG(FCY)$$

The distributions of REGLIFE and RELIF were determined for all batteries in the two sub-sets.

The DOD50 sub-set has 45 items including 9 that had not failed by the end of the test period. The maximum measured lifetime was 589 cycles, after which the test was discontinued. The median lifetime for the 45 items was 495 cycles, and the unfailed units were assigned a life of 625 cycles.

The DOD75 sub-set has 30 members with only one battery unfailed at the end of the test period. The median lifetime was 403 cycles, and the unfailed unit was assigned 600 cycles.

Figures 2 and 3 present the distributions of REGLIFE and RELIF for the DOD50 and DOD75 sub-sets of 45 and 30 items, respectively. Note that the DOD75 range is considerably broader than the DOD50 range in both cases.

Weibull Analysis.

The above groupings and assumptions are supported by a separate analysis based on Weibull failure distribution theory. All wearout failure cycle lives can be accurately represented by Weibull distributions, separately for each depth of discharge. The premature failures were not due to wearout from degradation of plate materials, as established for all other failures and as reasonably expected for the remaining unfailed batteries. Maximum cycles can also be estimated confidently.

Weibull Factors for Cycle Life
Failure Distributions

Depth of Discharge, %	25	50	75
Number of Samples	30	45	30
Number Failed	7	36	29
Weibull Shape Factor	13	8.9	6.6
Weibull Mean - cycles	630	480	410
Standard Deviation	60	65	70
Correlation Coefficient	0.96	0.96	0.98
Estimated Maximum - cycles	750	600	525

The strong wearout characteristic seen in the Weibull distribution is consistent with battery performance. It is an important measure to compare to the apparent wide range in numbers of cycles achieved at each DOD. Bode (1977) discusses failure distributions for lead-acid life data, with examples including the Weibull distribution.

Categorization.

The selection of any particular boundary for categorization depends on two things. One of these is the purpose of the categorization. For example, if a simple binary "better/ worse" is desired, the first-cut boundaries for Figures 2A and 2B might be -36 and 0, respectively. A second criterion is based on the observed performance of the selected boundary for pattern recognition classification.

DATA ANALYSIS

Definition of Features for Pattern Recognition.

The features used for pattern recognition lifetime prediction were taken from TRW documentation of the preliminary examination and initial acceptance tests applied to all 120 EV-106 batteries prior to commencing life-cycling testing. These included measurements of the specific gravities, battery weights, and volume of water required to achieve uniform levels for each cell/battery as received, as well as discharge capacity values over the 8 or 9 acceptance cycles.

These initial acceptance data were used to generate pattern features for each battery. The most useful features fell into 4 categories: initial specific gravity, initial water volume added, initial capacity trends, and transformed/ combined variables. A total of 10 features proved to be useful, and these are summarized in Table 1. All pattern recognition studies were conducted with standardized variables.

As expected, some of the features were highly correlated. However, as observed in previous studies (Thomas 1977; Sybrandt and Perone, 1972; Pichler and Perone, 1974) the use of statistically correlated features can be justified and

TABLE 1

Classification Features For Each EV-106 Battery
Based on EV-106 Acceptance Tests

NAME	TYPE	DESCRIPTION
	SPECIFIC GRAVITY	
AVSG		AVERAGE SPECIFIC GRAVITY 3 CELLS
	WATER VOLUME ADDED	
MXH		VOLUME FOR CELL REQUIRING MOST WATER
	INITIAL CAPACITY TRENDS	
INCAP		AVERAGE CAPACITY OF ACCEPTANCE CYCLES
MXCP		MAXIMUM CAPACITY FROM ACCEPTANCE CYCLES
MNCP		MINIMUM CAPACITY FROM ACCEPTANCE CYCLES
	TRANSFORMED VARIABLES	
AVSG2		$(AVSG)^2$
MXH2		$(MXH)^2$
SGH		AVSG*MXH
DLCP		MXCP - MNCP
INDL		INCAP/DLCP

useful for pattern recognition where normal distributions are not observed.

Feature Plots.

An examination of pattern distributions in feature space provides useful insight to the applicability of LDA or kNN classification techniques. For example, Figure 4 shows a feature plot of INCAP and SGH for the DOD75 sub-set, where class assignments were based on the optimum boundary for the REGLIFE distribution (discussed below). In this case the two classes are linearly separated in 2-d feature space. The LDA method works very well, but the kNN method does not, for this distribution.

Optimizing Class Boundaries From Lifetime Distributions.

This report focuses on the simple binary classification issue where batteries were divided into longer-lived and shorter-lived classes. Identification of these two classes appeared to be a realistic goal for practical applications of these methods to battery lifetime prediction. The method used to identify the optimum class boundaries from lifetime distributions involved, first, selecting arbitrarily a naturally--occuring break in the distribution. The boundary was then adjusted in either direction searching for maximum classification accuracy.

Classification Results.

Examination of Table 2 verifies that pattern recognition provides accurate prediction of lifetime class based on battery acceptance test data. Both the LDA and kNN methods proved useful, but the LDA method provided the most accurate lifetime classifications for all sub-sets, and only LDA results are included here. For each sub-set, overall

Table 2. SUMMARY OF CLASSIFICATION RESULTS WITH LINEAR DISCRIMINANT ANALYSIS.

(Long-lived batteries = class 1; short-lived = class 2)

DATA BASE SUB-SET							
DOD	NO. ITEMS	CLASS DISTRIBUTION (1) / (2)	CLASSIFICATION CRITERION/BOUNDARY	FEATURES REQUIRED	CLASSIFICATION RESULTS % CORRECT	%(1)	%(2)
50	39(a)	29 / 10	RELIF / (0.909)	(5) AVSG2, MIN2, SGH, INDL, INCAP	87.2	82.8	100
50	45	38 / 7	RELIF / (0.877)	(4) MIN2, SGH, INDL, INCAP	85.5	85.7	84.2
50	44(b)	32 / 12	REGLIFE / (-34.34)	(3) SGH, INDL, INCAP	81.8	78.0	92.0
75	30	16 / 14	RELIF / (0.977)	(2) SGH, INCAP	83.3	81.2	85.7
75	30	16 / 14	REGLIFE / (-15.04)	(2) SGH, INCAP	83.3	81.2	85.7
50 / 75	69(a)	57 / 12	RELIF / (0.878)	(4) MIN2, INDL, DLCP, INCAP	81.2	82.5	75.0

(a) Features of batteries with IAV = 20 removed from the data base. (All but one unfailed at end of test.)

(b) One battery (S/N = 16) removed from data base because of anomolously low lifetime for IAV = 20.

classification accuracy of about 85% was achieved. Best results were obtained for the DOD50 sub-set, where classification accuracy for short-lived batteries approached 100%.

There did not appear to be any significant advantage for either of the two lifetime normalization methods, REGLIFE or RELIF. Both worked well. However, only the RELIF distribution could be used for the DOD50/75 sub-set because the REGLIFE distributions for DOD50 and DOD75 were so different.

The size of the DOD50 sub-set was varied in these studies to examine the effects of various anomalies in the test items. These are footnoted in Table 2. One excluded test item was a battery (s/n 16) in the DOD50 sub-set which had an exceptionally low lifetime (438 cycles) for a low IAV of 20 A. By way of confirmation, an autopsy (Kraml 1982) of this battery revealed that the negative plates were "hard and dry", a condition not found in any of the other autopsies.

The optimum boundary values of REGLIFE and RELIF between short-lived and long-lived cells is shifted to larger values for the DOD75 sub-set compared to the DOD50 sub-set (Table 2). This results in a larger percentage of DOD75 batteries being categorized as "short-lived". This is consistent with the fact that actual depth of discharge was ~93% or greater, as previously noted. Thus, it is expected that the fraction of batteries which cluster together as a "short-lived" group is larger for the DOD75 sub-set. Also, the relatively poor classification accuracy obtained when DOD50 and DOD75 sub-sets are combined reflects the significantly different distributions of the two classes for the two sub-sets.

The most useful features for predictive lifetime classification appeared to be SGH and INCAP, based on the high frequency of their appearance in the minimum feature sets for

accurate classification. This observation is certainly consistent with the intuitive perception that differences in specific gravity, water added, and initial capacity trends should be meaningful predictors of battery life. It is clear, however, that the relationships between all features studied and battery cycle lifetimes are non-linear and multivariate.

Cumulative Capacity

The NASA/TRW tests also included measures of the cumulative Ah charge/discharge passed through each battery. This is a different measure of battery life that was not used in the pattern recognition analyses, but it probably would give similar results. The failure distribution data in the 3 depth of discharge subsets were well-fitted by Weibull distribution factors as valid as those for the cycle life data (Spindler, 1983). However, they were inversely related; that is, the lifetime capacity throughput increased as DOD increased. The Weibull mean life estimates for 25, 50 and 75% DOD were, respectively, 2000, 2900 and 3200 Ah compared to 630, 480 and 410 cycles. In our future work described in the next section we will be carefully studying these two different life measures for their implications in the design and use of both EV and L-L batteries.

OBSERVATIONS WITH THE GNB LOAD-LEVELING BATTERIES

Battery Characteristics.

A 500 kWh lead-acid load-leveling (L-L) battery was produced for EPRI by GNB Batteries, Inc. and installed at the Battery Energy Storage Test (BEST) Facility late in 1983. It will be under test for 6 or more months, with cycling for various utility and customer applications requiring from 1 to 5 hours discharge and providing 4 to 8 hours for recharge on a daily

basis. A service life of 8 years or 2000 cycles is warranted for up to 1 cycle per day, 5 cycles per week, 50 weeks per year, with energy efficiency greater than 70% over any consecutive interval of 50 cycles including equalization.

There are 330 cells assembled in 55 12-V modules. There are 3 strings each having 18 modules series-connected. The strings can be configured either in parallel to form a nominal 250-V battery, or in series at 750 V. One module is a spare for separate surveillance. The cells have a capacity of 2000 Ah or more at the 6 hour rate and will deliver approximately 1000 Ah at the 1 hour rate (50% DOD). Cells are built with 27 plates in a modified case of a standard type (160XL-27) used in fork-lift truck batteries.

Procurement specifications included factors based on the results of the previous EV-106 statistical studies. Factory production and formation operations were augmented with step by step data collection, providing cell dry and wet weights, specific gravities and amounts of acid or water added, and changes during the 5 factory capacity discharge/charge qualification cycles. Acceptance required all cells to be within +/- 10% of design capacity rating. Cells were numbered at time of assembly, and source information was recorded for the batches of pasted plates and grids. Cells were formed sequentially in corrals of 80 as production continued, with a final 5th corral of 20 cells including 10 extras for a total of 340. The module assemblies of 6 cells each provide for insertion of thermocouples to monitor temperature and to control operation below 43°C. Every cell is also equipped for entry of an air pulse to stir the electrolyte. This will reduce stratification and minimize overcharge and equalization losses.

Description of the Data Base.

We have organized a computer data base containing fabrication parameters and initial test results on the 340 production cells. Variations in raw material, fabrication, formation and cycling conditions are all documented. The first 4 batches containing 80 cells each, and the 5th containing 20 cells are referred to as Circuits 1 to 5.

Table 3 defines typical features extracted from the data base for statistical and pattern recognition analysis. The table provides shorthand notation for parameters referred to in this report. Multivariate analyses of these data provide insight to inherent correlations among the variables. These preliminary results are based entirely on the factory data.

Preliminary Observations.

The cell test measurements are affected by the formation circuits. There are significant differences in the mean values for 80% of the variables between some circuits. Some examples are tabulated of features which show significant differences (t-test, 99% confidence level):

MEAN VALUE BY CIRCUIT NUMBER

	1	2	3	4	5
AVCAP, %	93.3	93.1	98.2	100.7	99.4
SG2	1.251	1.273	1.267	1.265	1.267
EQWF, g	1720	800	228	274	460
AVSA	1.142	1.143	1.134	1.137	1.155

TABLE 3.

Data Features for GNB Cells Extracted from GNB Data Base

Feature	Definition
AVCAP	average capacity over 5 test cycles, %
AVSA	average SGA over 5 test cycles
CAPSLFA	total acid in cell after equalization before 5th test cycle
EQWC	acid added in equalization before 5th test cycle
EQWF	acid added in formation equalization step
INDL	AVCAP/RNGCAP
MNCAP	minimum capacity over 5 test cycles, %
MXCAP	maximum capacity over 5 test cycles, %
MXSA	maximum SGA over 5 test cycles
RNGCAP	(MXCAP - MNCAP), %
SGA	sp. gr. after discharge of each test cycle
SG2	sp. gr. prior to formation equalization step
SG4	sp. gr. prior to equalization between 4th & 5th test cycles
SHPSLFA	total acid in cell as shipped.

Some of the observed variations of test data can be correlated with whether "old" or "new" grids or pasted plates were used in cells. Results of correlation analysis, t-test, and cluster analysis all demonstrate that these fabrication parameters have a profound influence on measured test values. Thus, in addition to the five sub-sets due to the formation circuits, there are 4 other subsets:

sub-set	circuit	cells	grid	pasted plates
(a)	1	1 - 15	old	old
(b)	1	16 - 80	old	new
(c)	3	161 - 218	old	new
(d)	3	219 - 240	new	new

Table 4 lists those observed features which were significantly different, and those which were not, for the two subsets in both circuits 1 and 3. It is not yet clear whether significant differences in items such as specific gravity are entirely due to inherent cell properties, or due to variations in measurement procedures or operators.

For circuit 1, when cluster analysis was conducted using only those variables showing the most significant differences between sub-sets (a) and (b), (MXCAP, AVSA, MXSA, EQWF, EQWC, SG4), 2 clusters were observed. Cluster A contained cells 1 - 13, 15, 16, 45, 46, and 48; cluster B contained the rest. The breakdown of clusters corresponds closely to the breakdown of two subsets due to old/new grids and pasted

TABLE 4.

Comparisons of Data Features for BNB Cells in Various Sub-sets

(A) Features Showing Significant Differences (99% confidence level) for sub-sets of BOTH Circuits 1 and 3.

	Mean Values			
	Sub-set		Sub-set	
Feature	(a)	(b)	(c)	(d)
AVCAP, %	94.0	92.0	97.0	101.7
MXCAP, %	97.4	95.5	100.1	104.9
MNCAP, %	91.3	89.5	94.1	98.6
MXSA	1.154	1.152	1.142	1.148
EQWF, g	1483	1732	587	-198
EQWC, g	-115	57	-322	-415
BG4	1.286	1.280	1.284	1.287

(B) Features Showing NO Significant Differences (99% confidence level) for Sub-sets of BOTH Circuits 1 and 3.

	Mean Values			
Feature	(a)	(b)	(c)	(d)
INDL	16.8	15.7	16.6	16.7
RNGCAP, %	6.1	6.0	6.0	6.3
BHPSLFA, Lb	24.8	24.9	24.7	25.2
CAPSLFA, Lb	24.5	23.9	24.3	24.7

plates. For circuit 3, when cluster analysis was conducted using only those variables showing the most significant differences between subsets (c) and (d), (SG2, EQWF, AVCAP, RNGSGA, MXCAP, MNCAP, MXSA), 2 clusters were observed. Cluster C contained cells 162 - 216; cluster D contained the rest. Just as observed for circuit 1, the breakdown of clusters corresponds closely to the breakdown of the old/new grids and pasted plates.

Although the observed clustering within circuits 1 and 3 for the features selected above may have been predictable, the results establish the credibility of the cluster analysis technique for further studies. Thus, the existence of other clusters when different feature sets are used may be indicative of other physical/chemical factors of which we are unaware, and which may be predictive of different classes of cell performance. When cluster analyses of cells in circuits 1 and 2 were conducted, using random combinations of uncorrelated variables, other clusters appeared to emerge, based on consensus results of 5 - 8 separate analyses using different feature sub-sets. The implications of these results are uncertain. We will probably not recognize their significance until cell performance and/or lifetime results are obtained from the BEST Facility. However, because the features used for cluster analysis are similar to those used for lifetime prediction with the TRW lead-acid data base, it is exciting to speculate that the observed clustering may be predictive of different classes of lifetime.

CONCLUSIONS

The study of the TRW data base clearly demonstrated the feasibility of predictive lifetime classification for uniformly fabricated lead-acid batteries. The accuracy of predictive classifications was sufficiently high, particularly for the identification of short-lived batteries, that

the practical application of this method should be undertaken.

Perhaps of more importance is the fact that this type of study may provide new insight to factors which affect battery life--as reflected in the useful features for predictive lifetime classification. This is a primary goal of the current program correlating GNB cell performance with fabrication and initial test data.

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LIST OF FIGURES

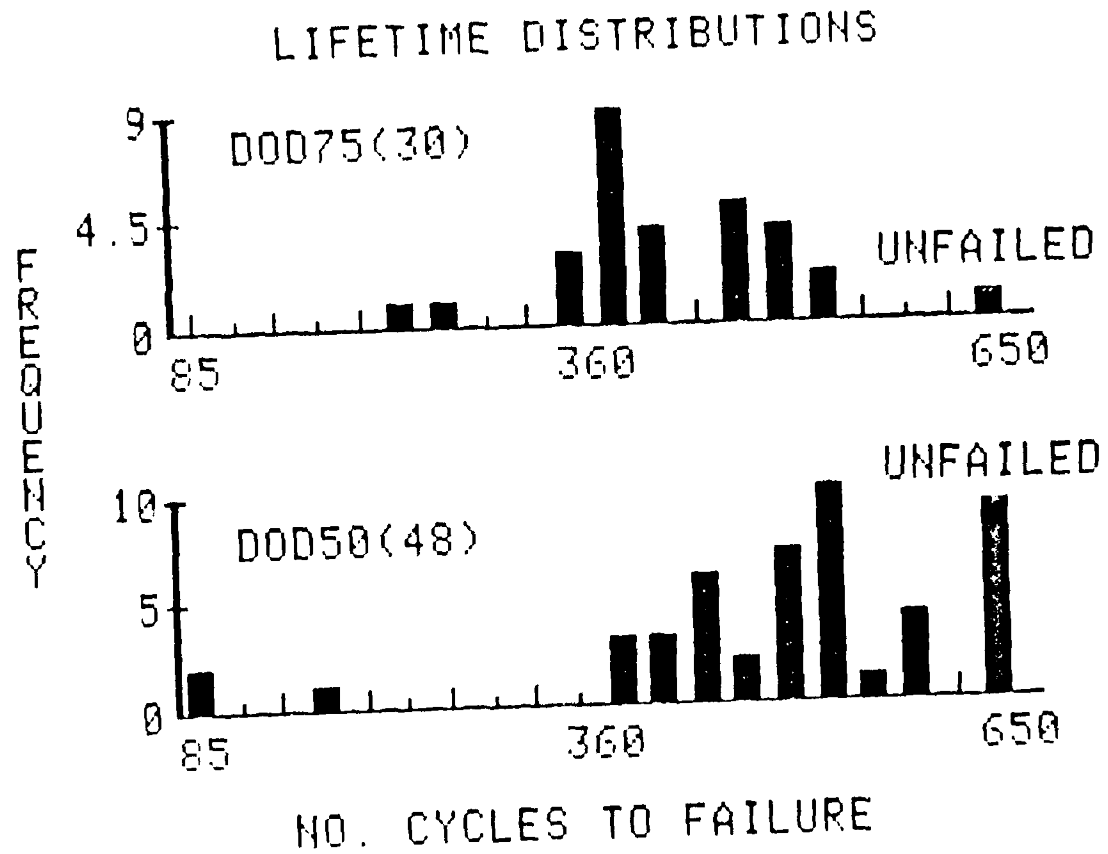

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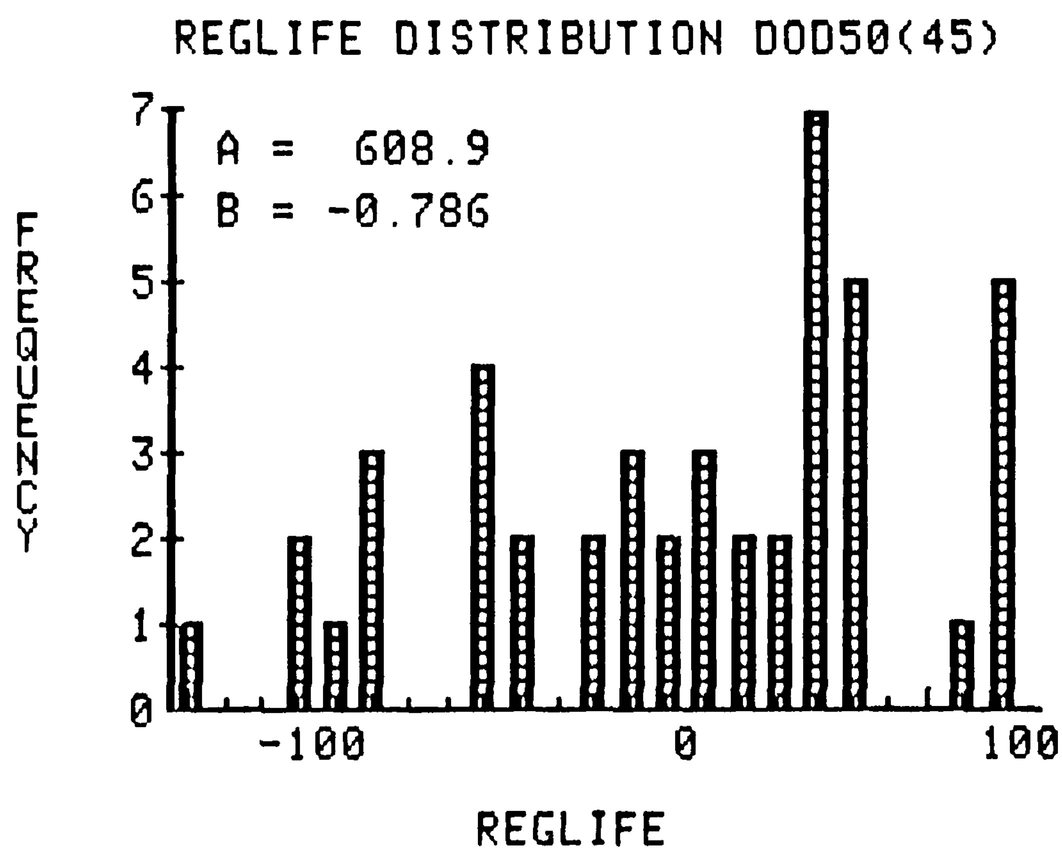
FIG. 1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100
REGLIFE

FIG. 2A

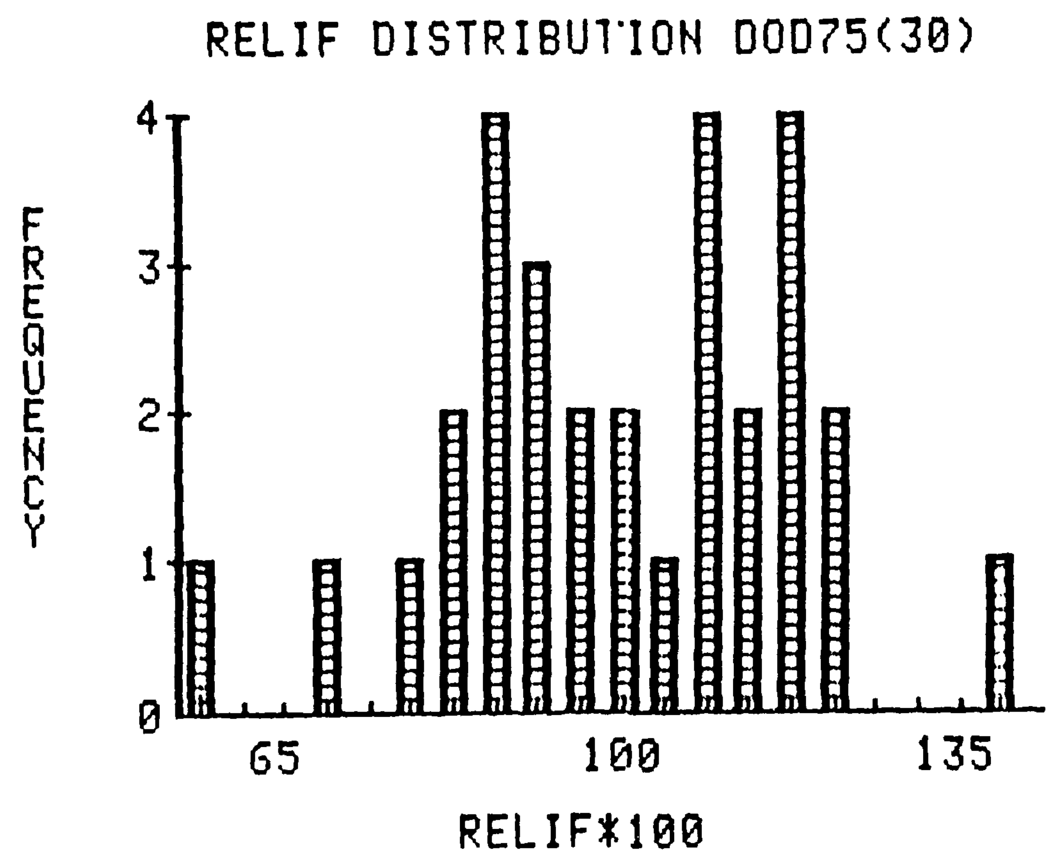
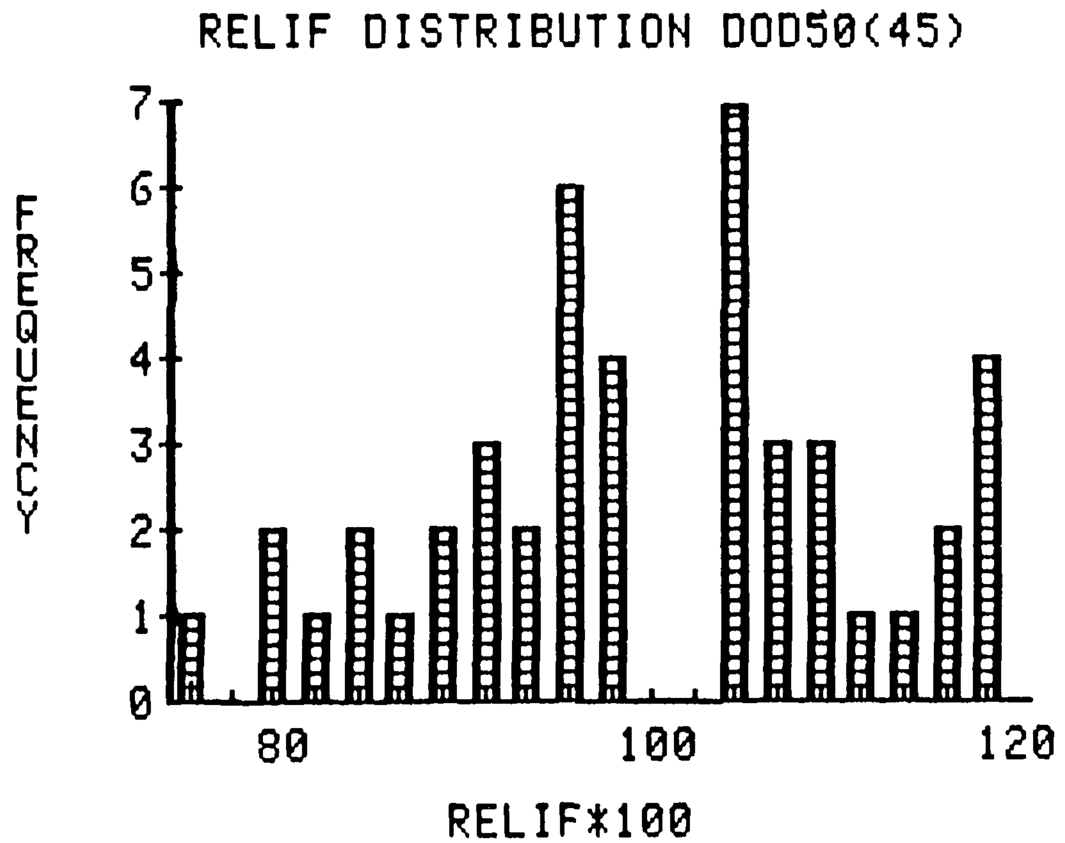


FIG. 3B

REGLIFE

FIG. 2B


RELIF DISTRIBUTION DOD50(45)
FREQUENCY
0
1
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7
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120
RELIF*100

FIG. 3A

RELIF DISTRIBUTION DOD75(30)

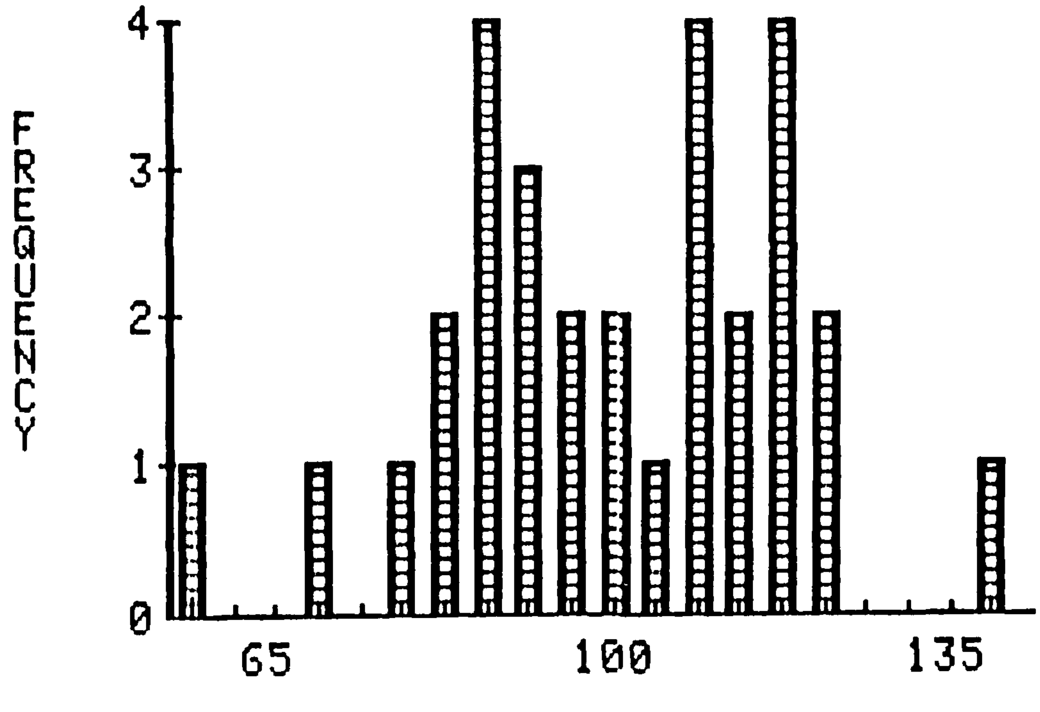

FIG. 3B

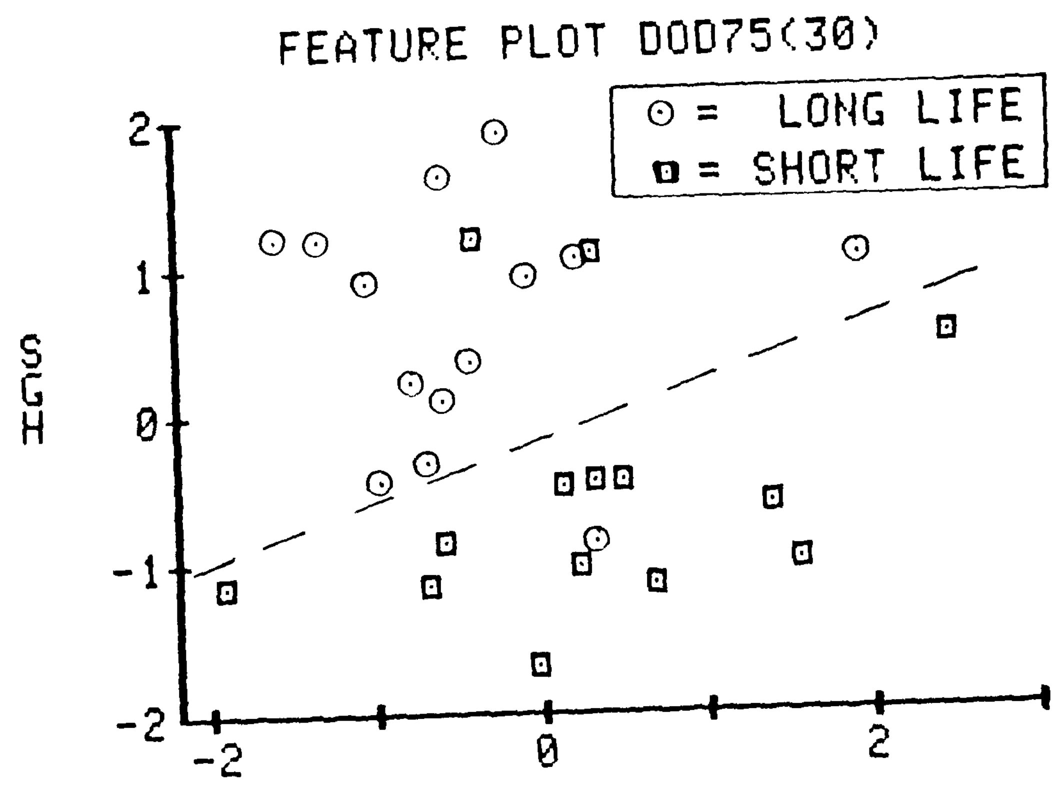
FEATURE PLOT DOD75(30)
⊙ = LONG LIFE
▫ = SHORT LIFE
SGH
2
1
0
-1
-2
-2
0
2
INCAP

FIG. 4

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